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Real-Time 2D Mapping and Localization Algorithms for Mobile Robot Applications

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Abstract. The purpose of this paper is to show an approach in 2D localization and real-time mapping for robot applications that combine the Particle Filter algorithm, Extended Kalman Filter (EKF), and Iterative Closest Point (ICP). The closing loop method is added and shows satisfactory 2D mapping and localization results. We tested our approach to large floor buildings. For testing, we used a two-wheeled differential drive robot equipped with an optical encoder, laser scanner and gyroscope. Test results show that an accurate map of large high-rise buildings can be produced. Real-time mapping can reach a resolution of 5 cm. Automatic localization of cellular robots in unknown environments is one of the most fundamental problems in robot navigation. This is a complex problem due to the stringent requirements on cellular robots, especially those relations to accuracy, durability, and computational efficiency. The conclusions from this study can help in developing real-time 2D mapping for robot applications that process 2D cloud points directly.

1. Introduction

One of the most fundamental problems in the robotics navigation field is self localization and mapping of robots in unknown environments [1]. This problem is known as the Simultaneous Localization and Mapping (SLAM) problem [2]. A SLAM algorithm consists of exploring the unknown environment to build or updating its map and to determine the position of the robot on the map based on a series of actions and observations [3]. There are many applications of SLAM solution, such as in autonomous vehicles [4, 5], minimal invasive surgery [6, 7] and harvesting [8, 9]. SLAM is a complex problem because of the strict requirements on mobile robots, especially related to robustness, computational efficiency and algorithm accuracy [10]. Although the position of the robot can be obtained using Global Positioning System (GPS) signals, they have limitations such that they can be blocked by buildings or thick clouds [11]. The SLAM method can be used to solve the limitations of this GPS signal [12].

The Extended Kalman Filter (EKF) and the Particle Filter [13] are two popular estimation methods commonly used in the SLAM algorithm. The EKF SLAM algorithm is based on two main assumptions [14]: first, objects or landmarks in the environment should be uniquely associated using sensor measurements (this process also known as data association problems), and second, the noise in robot trajectories and sensor measurements following a Gaussian Distribution. The use of Particle Filters in SLAM problems was first performed by Murphy [15] and Doucet[16]. The advantage of particle filters over EKF is that they do not require linearization because particle filters use multiple samples to obtain state estimates. Another advantage is that particle filters can process raw data from sensors without the need for feature or landmarks detection. Each particle in the samples represents the path and the map of the robot. However, the disadvantage of particle filters is the increase in the cost of calculation and use of memory. Montermerlo proposed the application of Rao-Blackwellized Particle Filters (RBPF), derived from particle filters, and named them FastSLAM [17]. By using a predetermined landmark in

the environment, FastSLAM can compensate for the amount of memory usage by sharing maps between particles. FastSLAM uses laser scanning as a robot sensor and adopts landmark-based maps. FastSLAM 1.0 is the first version of this algorithm. FastSLAM 1.0 uses EKF to keep maps based on landmarks of each particle. FastSLAM 2.0 is the second version of this algorithm. FastSLAM 2.0 uses EKF to produce a better distribution of the particle filters [18].

The paper purpose is to demonstrate one approach in a real time 2D mapping and localization for a robotic application. In this research, we integrate the EKF, the Particle Filter and Iterative Closest Point (ICP) [19] algorithm to improve the SLAM performance. We also add the loop closure method [20] to obtain more satisfying 2D mapping and localization results. Then, our algorithm is tested on a large building. A LabVIEW Robotics Starter Kit with optical encoders, gyroscope and a Hokuyo URG Series Laser Range Finder is used for testing. We compare the test result with EKF-SLAM and Particle Filter.

2. Method

The propose SLAM system can be described as shown in Figure 1. We have developed the algorithm proposed by [21-23] by adding a particle filter algorithm. The system inputs are encoders, gyroscope and laser scanner results. The system output is the SLAM gridmap and robot position. The main component of the EKF SLAM algorithm is detecting landmarks around the robot path. Landmark is a collection of unique features extracted based on laser scanner results. Each landmark data contains information of the x and y positions of the landmarks from the position of the robot. Every time a landmark is detected, the system will compare it to previous created landmarks. If it is recognized, an estimate is calculated on where the robot's location relative to where it was located when the landmark was created. If a recognition is not made, the module attempts to create a new landmark.

The proposed EKF SLAM system is a feedback system that takes a new pose estimated from a particle filter, a new pose estimated from odometry data and a new pose estimated from scan matching as inputs, to merge and compared to predict a new robot position. We use the EKF algorithm as proposed by [14]. For the particle filter algorithm we used, we refer to [23]. For matching scan modules, we apply the Iterative Closest Point (ICP) algorithm as described in [14] (Figure 1).
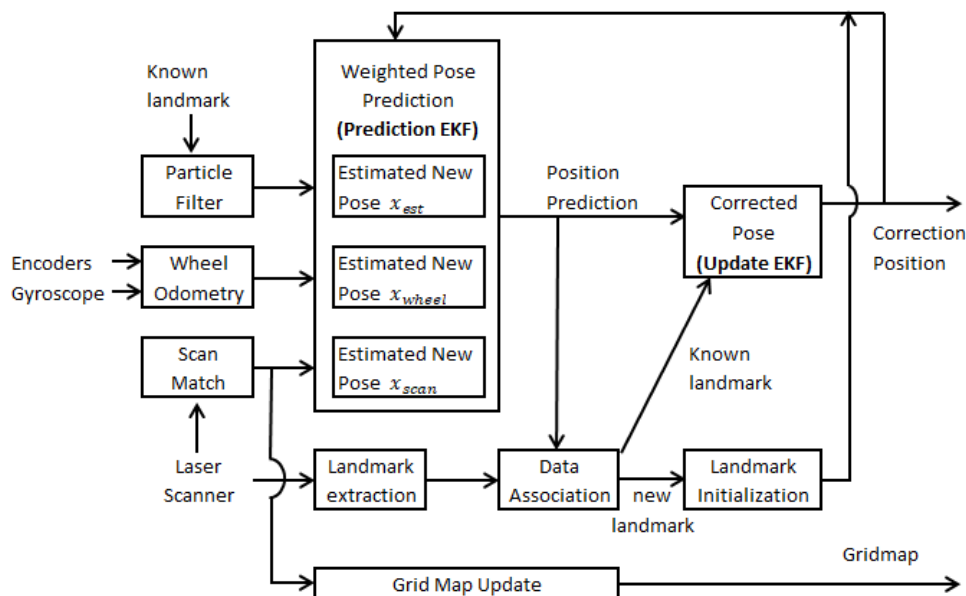

Figure 1. Block diagram of propose SLAM

In the occupancy grid map, the environment consists of a number of grids of the same size. Each grid is called a cell. The occupancy probability of each cell is calculated and represented using the gray value. The algorithm uses the inverse sensor model. As shown in Figure 2, the occupancy value of each cell depends on the measured distance. Coincident cells are considered to be occupied (white cells) and the

cells in between are considered empty (black cells). In map matching, a local map containing the current measurement is compared to a global map that has past measurement.
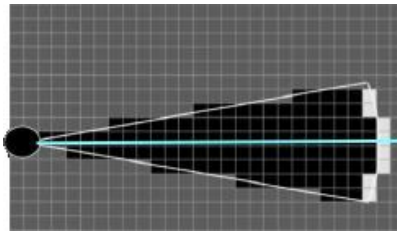

Figure 2. Cells in the measurement range of the sensor are marked as occupied and the cells in between are marked as empty.

3. Results and Discussion

To prove its effectiveness, we use the NI LabVIEW Robotics Starter Kit to implement the proposed algorithm. The specifications of the hardware we use will be explained first. Then, we will present the test results of the proposed algorithm.

3.1. Hardware

We tested the algorithm that we proposed using the NI LabVIEW Robotics Starter Kit. As an integrated control platform, this robot uses NI Single-Board RIO 9631. The NI Single-Board RIO 9631 is programmed using NI LabVIEW Robotics Module. NI Robotics Starter Kit has two Pitsco Education TETRIX 4 inch wheels in addition to one Omni-wheels for steering. The NI Robotics Starter Kit also has two 152 RPM DC motors. The 400 PPR optical quadrature encoder is installed in each DC motor on the front wheel robot side.

At present, in sensor-based robotic navigation methods, the laser scanner is one of the most accurate sensor that can be used [24]. This is because the laser scanner has a high-accuracy, wide-angle high resolution that provides the optimal solution for cellular robots. We use Hokuyo URG-04LX as a laser scanner. The measurement range of this sensor is between 2 to 560 cm with a linear resolution of 1 mm and angular resolution to 0.36^o with field of view is 240°. The time needed to perform an analysis is 100 ms because the spindle motor is rotating at 600 rpm [25].

Using a wireless connection, NI LabVIEW Robotics is connected to a laptop. Instead of a cable connection, using a wireless connection will make the movement of the robot unrestricted. To send or receive data signals from or to a laptop, a wireless router is used. To provide power requirements for additional sensor components, DC to DC conversion is used to convert the 12 V DC battery voltage to 5 V DC. The final assembly of all components in the Starter Kit NI LabVIEW 1.0 is shown in Figure 3.
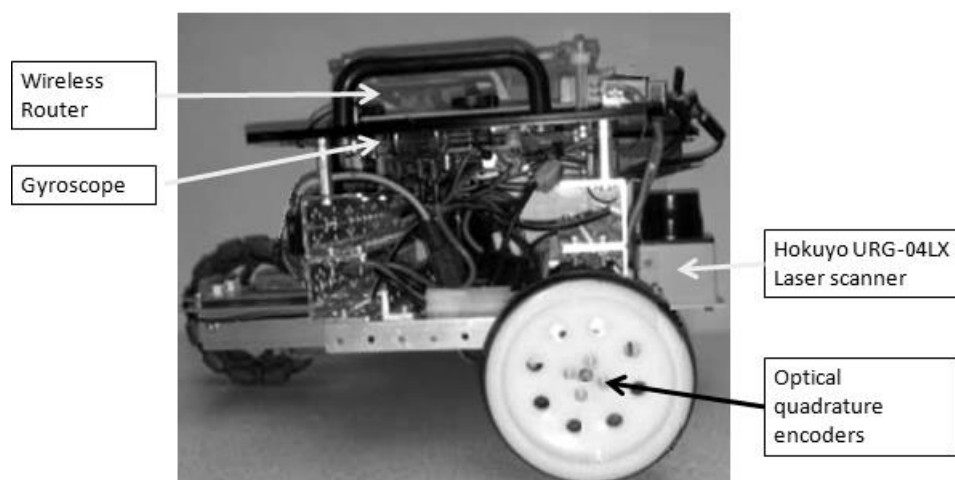

Figure 3. NI LabVIEW Starter with laser scanner, encoders and gyroscope

3.2. Test Result
A Test has been run in the UNIKOM building on the 12th floor. The robot is driven manually at medium speed while the proposed SLAM algorithm is active. Figure 4 shows a photo of the robot when making a map on the testing floor.

Figure 4. Robot when making a map

Figure 5 shows the actual map of the testing floor. A dark gray area is an area that is passed and then mapped by a robot using a laser scanner.
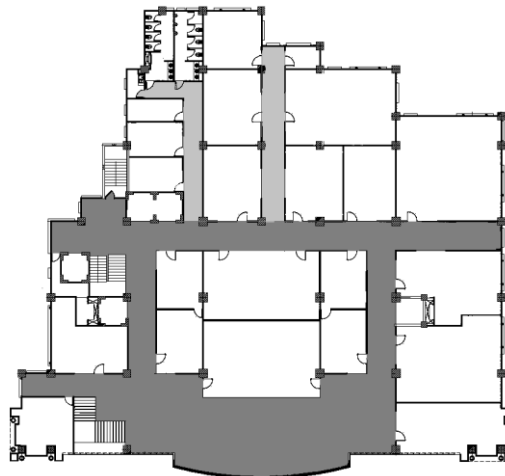

Figure 5. Real map of the testing floor

The grid map results from the proposed SLAM algorithm are shown in Figure 6. And Figure 7 shows the results of a comparison between prediction trajectory of the proposed SLAM algorithm and the real trajectory. A solid line is a prediction trajectory, and the dash line is a real trajectory of a robot. A circle image on the corners of a wall is a landmark that is detected.

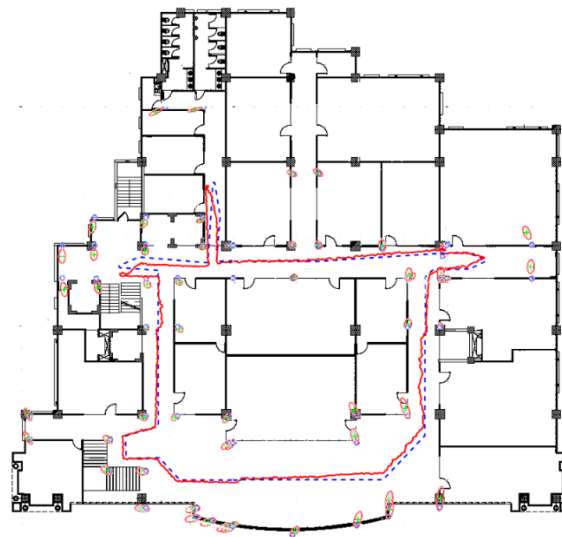**Figure 6**. Grid map result from the propose SLAM

Figure 7. Trajectory prediction from the propose SLAM

The total trajectory traveled by the robot is about 94 meters. The total area mapped by the robots is about 393 square meters. The resolution produced by the proposed algorithm reaches 5 cm. This resolution is better than obtained in [1], where the resolution is still in the range of 24 cm.

3.3. Comparison with EKF SLAM and Particle Filter SLAM.

In Figure 8, we present the performance comparisons between our algorithm with odometry, EKF SLAM and Particle Filter. The performance is measured as the average error between prediction position and the true position. This graph shows that EKF-SLAM, the Particle Filter and the proposed algorithm have better error distances than the odometry algorithm. Particle Filter performance is better than EKF-SLAM. And the average error value of the proposed algorithm is less than the Particle Filter. These results correspond to the results obtained by [26-27], where it was reported that the performance of FastSLAM was better than EKF-SLAM and odometry, whereas the performance of EKF-SLAM was better than odometry.
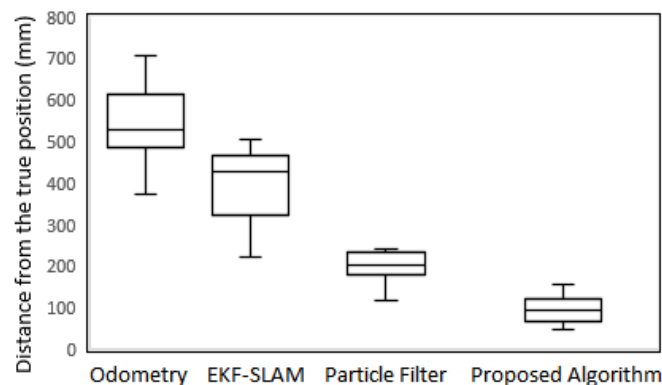
Figure 8. Boxplots of odometry, EKF SLAM, Particle Filter and Propose SLAM performance

4. Conclusion

A test results show that accurate maps from large floor distance can be generated. Real time mapping can reach a resolution of 5 cm. It has been shown that the proposed algorithm has an average error distance to the actual position that is smaller than the Particle Filter and EKF SLAM algorithm. However, this study has not compared computational time and memory complexity between these algorithms. This work is expected to help in developing mapping for robot applications that process 2D cloud points in real time.

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